Comparative Analysis of Data Mining Techniques for Classification of Student's Learning Styles

Renato R. Maaliw III, Melvin A. Ballera, Shaneth C. Ambat and Menchita F. Dumlao

***Abstract* — This study focused on the comparative performances of different classification algorithms provided in WEKA such as Neural Network, Naïve Bayes, PART and J48 Decision Tree classifier in classifying students learning styles. The student's behavior and navigational patterns have been observed while using a learning management system and eleven attributes have been found to be significant in classifying student's learning styles based on the Felder-Silverman learning style model. A total of 60,158 rows of log and interaction data from 565 students of Computer Programming 1 Moodle online course have been extracted. A 10-fold cross validation was used to evaluate the selected classifiers. Classification accuracy, training errors and kappa statistics have been observed to measure the performance of each classifier. The experiment showed that the J48 decision tree technique had the highest collective average value of correctly classified instances at 87.56% accuracy and it could be used to classify the learning styles of students in a Learning Management System.**

Keywords—Learning management system; Learning styles; Felder-Silverman learning style model; Educational data mining

I. INTRODUCTION

The use of web-based education systems has grown exponentially in the last few years. It is encourage by the fact that neither students nor teachers are bound to a specific location and that resulted of computer-based education which is virtually independent of any specific hardware platforms. Specifically, collaborative communication tools are becoming widely used in educational contexts. This results to Learning Management Systems (LMS) to be currently installed by more and more universities, community colleges, schools, businesses, and even individual educators in order to add web technology to their courses and to supplement traditional classroom settings.

There are increasing research interest in utilizing data mining in the field of education. This new emerging discipline is known as Educational Data Mining (EDM). Its primary concern is developing methods for exploring the diverse and unique types of data that comes from educational settings.

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At present, Learning Management Systems (LMS) increasingly serve as an important infrastructure of most universities that enable teachers to provide students with different representations of knowledge and to enhance interaction between teachers and students, and even amongst students themselves. Learning Management Systems usually provide online tools for assessment, communication, uploading of content and various features. Whilst traditional teaching methods, such as face-to-face lectures, tutorials, lab assignments, and mentoring remain dominant in the educational sector, universities are investing heavily in learning technologies, to facilitate improvements with respect to the quality of learning [1]. Despite the ever-increasing practice of using e-learning in educational institutions, most of these applications perform poorly in motivating students to learn. There are many issues which are not addressed due to very complex and varying ideas in the development. It fails to meet the needs of students and fail to serve the ultimate goal of having on-line learning [2].

But what is almost completely overlooked is a vast collection of data that resides inside these specific environments. All this data represents a potentially valuable source which is not adequately considered. The data stored in these LMS can be used to improve the learning and pedagogical process to make it more efficient for both teachers and learners. Specifically, it can be used in the identification of students' learning styles (LS) to provide adaptation to LMS's course design and content to match the student's preference when it comes to their learning styles. Notable educational theorist and researchers consider learning style as an important factor that affects the learning process. Understanding how different individual learn is the key to a successful teaching and learning.

The research is based on a widely accepted theory that each learner has an individual or specific learning style. A learner with specific learning style can face difficulties while learning, when their learning style is not supported by the teaching environment thus the research focuses on the identification of student's learning styles using data mining techniques based on their behaviors on a LMS and providing adaptation strategy in order to adapt to their learning styles. In terms of learning style model, Felder-Silverman learning style model (FSLSM) was used for the reason that is often used in technology enhanced learning [3]. Moreover, FSLSM describes the learning style of a student in more detail, distinguishing between preferences on four dimensions as compared to other learning style models that classify learners in only a few groups.

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II. RELATED LITERATURE

A. Learning Styles

A learning style is a student's consistent way of responding to and using stimuli in the context of learning. Reference [4] defines learning styles as the composite of characteristic cognitive, affective, and physiological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment. Reference [5] defines learning style as those educational conditions under which a student is most likely to learn. They are not concerned with what learners learn, but rather how they prefer to learn. Learning styles are points along a scale that help discovers the different forms of mental representations. When individual tries to learn something new they prefer to learn it by listening to someone, talking to someone, or perhaps they prefer to read about a concept to learn it, or perhaps would like to see a demonstration.

Learning styles can be defined, classified, and identified in many different ways. It can also be describe as a set of factors, behaviors, and attitudes that enhance learning in any situation. How the students learn and how the teachers teach, and how the two interact with each other are influenced by different learning styles. Each person is born with and has certain innate tendencies towards a particular style, and these biological characteristics are influenced by external factors such as cultures, personal experiences, and developments. Each learner has a different and consistent preferred ways of perception, organization and retention.

These learning styles are the indicators of how learners perceive, interact with, and respond to the learning environments. Students have different styles of learning, and they learn differently from one another. There are sufficient evidences for the diversity in individual's thinking and ways of processing various types of information, and shown that students will learn best if taught in a method deemed appropriate for their learning style [6].

B. Felder-Silverman Learning Style Model

One of the most widely used models of learning styles is the Index of Learning Styles (ILS) [7] developed by Richard Felder and Linda Silverman. The Felder-Silverman Learning Style Model (FSLSM) unlike other model is based on tendencies, indicating that learners with a high preference for certain behavior can also act sometimes differently. FSLSM [8] is used very often in advanced learning technologies and technology-enhanced education. According to reference [9], the FSLSM model is most appropriate for multimedia courseware and online-teaching. Reference [10] confirmed this by conducting a comparison of learning models with respect to the application in Web-based learning systems. The result of their research confirmed that the use of FSLSM is the most appropriate model for technology-enhanced education environments. There are four dimensions in FSLSM such as Perception, Input, Information Processing and Understanding. Each learner is characterized by a specific preference for each of these dimensions.

These dimensions are based on major dimensions in the field of learning styles and can be viewed independently from each other. They show how learners prefer to process (active/reflective), perceive (sensing/intuitive), receive (verbal/visual), and understand (sequential/global) information. While these dimensions are not new in the field of learning styles, the way in which they describe a learning style of a student can be seen as new and innovative. While most learning style models, which include two or more dimensions, derived statistically prevalent learner types from these dimensions such as the models by Myers-Briggs [11], Gregorc [12] ,Kolb [13], and Honey and Mumford [14].

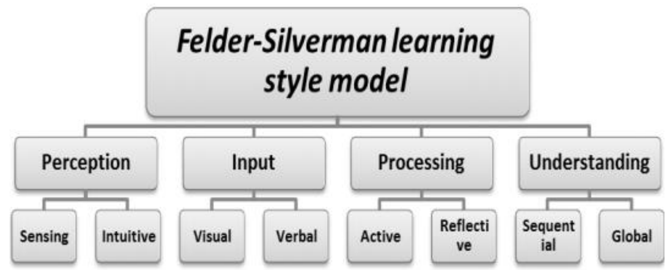

Fig. 1. Felder-Silverman learning style model.

The *active/reflective* dimension is analogous to the respective dimension in Kolb's model [15]. Active learners learn best by working actively with the learning material, by applying material, and by trying things out. Furthermore, they tend to be more interested in communicating with others and preferred to learn by working in groups where they can discuss about the learned material. In contrast, reflective learners prefer to think about and reflect on the material. Regarding communication, they prefer to work alone.

The *sensing/intuitive* dimension is taken from the Myers-Briggs Type Indicator [11] and has also similarities to the sensing/intuitive dimension in Kolb's model [13]. Learners with a sensing learning style prefers to learn facts and concrete materials, using their sensory experiences of particular instances as a primary source. They like to solve problems with standard approaches and also tend to be more patient with details. They tend to be more practical than intuitive learners and like to relate the learned material to the real world. In contrast, intuitive learners prefer to learn abstract learning material, such as theories and their underlying meanings, with general principles rather than concrete instances being a preferred source of information.

The third, *visual/verbal* dimension deals with the preferred input mode. The dimension differentiates learners who remember best what they have seen (e.g. pictures, diagrams, flow-charts and so on), from learners who get more out of textual or text-based representations, regardless of the fact whether they are written or spoken.

In the fourth dimension, learners are distinguished between *sequential and global* way of understanding. This dimension is based on the learning style model by Pask [16], where sequential learners refer to serial learners and global learners refer to holistic learners. Sequential learners learn in small incremental step and therefore have a linear learning progress. They tend to follow logical stepwise paths in finding solutions. In contrast, global learners use a holistic thinking process and learn in large leaps. They tend to absorb learning material almost randomly without seeing connections but after they have learned enough material they suddenly get the whole picture. Because the whole picture is important for global learners, they tend to be more interested in overviews and in a broad knowledge, whereas sequential learners are more interested in details.

III. METHODOLOGY

A. Context, Participants and Learning Style Questionnaire

The study is based on data sets from Computer Programming 1 course which is taught during the first semester for Computer Technology course in Southern Luzon State University. Aside from traditional classroom setup, the course is supplemented by a Moodle [17] course that is composed of five chapters that includes learning objects ranging from textual, visual, concrete and abstract materials. There are also different exercises that allow students to practice their programming skills. Self-assessment tests were also provided for each chapter overall. Students also were encouraged to use the forums in order to interact and solve problems with other students during the duration of the course. This particular course was selected for the investigation of individual learning styles for it is found to have large number of enrolled students in the Moodle course.

The study used the acquisition of data coming from the LMS database. Specifically, the data from student's logs and activities on the LMS were carefully examined. The student's learning styles that are used in the data sets are obtained by using the Index of Learning Styles (ILS) questionnaires that are provided in the FSLSM. These learning style questionnaires were answered by the students who were previously enrolled and completed the selected course.

A total of five hundred sixty five (565) students were able to fill the ILS questionnaire to determine their learning styles. Each question in the questionnaire was carefully explained to the students and they have been given ample amount of time to answer the questionnaire to avoid contaminating the data. Table 1 shows the learning styles' distribution for all dimensions of the FSLSM without considering the degree of learning style preference.

TABLE I. DISTRIBUTION OF LEARNING STYLES BASED FROM ILS

Dimension	Learning Style	No. of Students	Percentage
Processing	Active	287	50.80%
	Reflective	278	49.20%
Perception	Sensing	358	63.36%
	Intuitive	207	36.64%
Input	Visual	401	70.97%
	Verbal	164	29.03%
Understanding	Sequential	289	51.15%
	Global	276	48.85%

B. Learning Styles Mapping and Learner's Behavior in LMS

In this section, a mapping between learning styles and learner's behavior are presented through their relevant interaction logs in the LMS. The goal of this section is to define the features that can be extracted from the LMS logs which correspond to the learning style behavior of the learners. Table 2 provides the lists of the learning style mapping of relevant student's behavior in a LMS.

The features were mapped based from the Felder-Silverman Learning style model [8]. These sets of relevant behaviors were extracted from the LMS database to construct the data sets.

TABLE II. LEARNING STYLE MAPPING OF RELEVANT STUDENTS' BEHAVIOR

Learning Style	Relevant Behavior	Attribute Name	Attribute Value
Active	Post more often in discussion forum	forum_posts	no. of posting in forum
	Perform more self-assessment tests	self_assesment	no. of viewed post in forum
Reflective	Reading post but rarely posting by themselves	forum_view	no. of viewed post in forum
	Prefers learning material in textual form	text_materials	no. of visits
Sensing	Prefers concrete learning materials (facts, data)	concrete_materials	no. of visits
	Prefers examples	examples	no. of visits
Intuitive	Prefers abstract learning material (definition, theories, syntax, flowcharts)	abstract_materials	no. of visits
	Prefers to review answers in graded exercise tests	exercises_rev	no. of attempted answer reviews
Visual	Prefers learning materials supplemented with pictures, diagrams, graphs	visual_materials	no. of visits
	Prefers learning materials presented in a video format	video_materials	no. of visits
Verbal	Prefers learning material presented in text or audio	text_materials	no. of visits
	Post more often in discussion forum	forum_post	no. of posting in discussion
Sequential	Prefers to go through the course step by step (linear way)	nav_pattern_dist	sequence of navigational pattern
Global	Prefers overviews, outlines	course_overviews	no. of visits
	Prefers to learn in large leaps by skipping learning material & jumping to more complex materials (non-linear way)	nav_pattern_dist	sequence of navigational pattern

C. Data Preprocessing, Transformation and Attribute Value Extraction

Every logs and activities of all students are recorded in the LMS database. Primarily, LMS such as Moodle provides a module for extraction of user logs and activities for a specific course by exporting to varieties of file formats such as Microsoft Excel (*.xlsx) file. The table is comprised of data labels such as 'Time', 'User Full Name', 'Affected User', 'Event Context', 'Event Name', 'Description', 'Origin' and 'IP Address'. Data preprocessing phase was performed by reducing the log file which was cleaned by removing all unnecessary data. Interaction logs of each target students were extracted to produce a reduced log file that only contains the data labels of 'User Full Name', 'Event Context', 'Event Name' and 'Type'.

The reduced log file extracted contains 60,158 rows of student logs and activities for the course that were used in classification of individual learning styles in the study. As can be seen in Figure 2, a 'Learning Object Type' field has been created in order to identify as to what type of learning object each particular student interacts with. Identification of learning object type in the course was also mapped in order to identify as to what kind of learning object each truly represents based on the learning object literature types whether textual learning materials, visual learning materials, abstract learning materials, concrete learning materials and examples. These learning object type identification are evaluated by educational experts. It is necessary to distinguish these learning object types in order to effectively create data sets in inferring student's learning styles.

User full name	Event context	Event name	Learning Object Type
Beneluz Abustan	Page: Chapter 1 Overview	Course module viewed	course_overviews
Beneluz Abustan	Page: C++ Terminology	Course module viewed	abstract_materials
Beneluz Abustan	Page: Assignment Statements	Course module viewed	text_materials
Beneluz Abustan	Page: Assignment Statements	Course module viewed	text_materials
Beneluz Abustan	Page: Literals	Course module viewed	text_materials
Beneluz Abustan	Page: Literals	Course module viewed	text_materials
Beneluz Abustan	Page: Naming Constants	Course module viewed	text_materials
Beneluz Abustan	Page: Arithmetic Operators and Expressions	Course module viewed	text_materials
Beneluz Abustan	Page: Arithmetic Operators and Expressions	Course module viewed	text_materials
Beneluz Abustan	Page: Type Casting	Course module viewed	text_materials
Beneluz Abustan	Page: Output Using cout	Course module viewed	visual_materials
Beneluz Abustan	Page: New Lines in Output	Course module viewed	visual_materials
Beneluz Abustan	Page: Input using cin	Course module viewed	video_materials
Beneluz Abustan	Quiz: Exercise 1	Quiz attempt reviewed	exercises_rev
Beneluz Abustan	Quiz: Exercise 1	Quiz attempt reviewed	exercises_rev

Fig. 2. Reduced log data for the Computer Programming 1 (Moodle) Course

The next phase in the construction of the data sets is data transformation. The reduced log data in Microsoft Excel format is transformed and converted to a Microsoft Access file (*.accdb) format in order to easily aggregate the total number of interaction a particular learner to each learning objects. An aggregate SQL statement commands was used to extract the needed values for data mining and analysis. Derived variables was extracted through calculating and accumulating variable data such as number of visits, number of posts, and number of exercises review answer review attempts, and number of completed assessment test to name a few.

Figure 3 illustrates an example result of aggregated data for a particular learning using SQL queries.

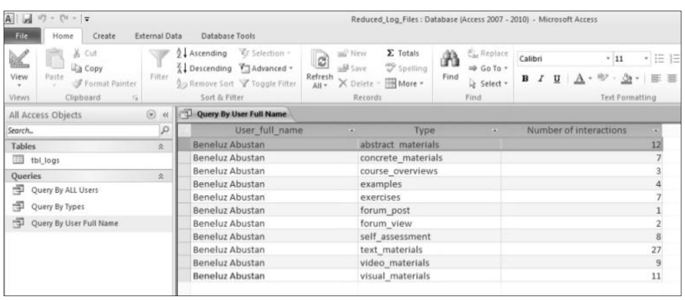

Fig. 3. Aggregated number of interaction of learner to a learning object

The final phase in the construction of data sets is to arrange the derived values of number of interactions of the students to a specific learning object. It was arranged and categorized based from the learning behavior pattern mapping in Table 2. An excerpt of final data set construction is depicted in Figure 4. Additional data field was created to accommodate the reported learning styles of each student based from their answers from ILS questionnaire.

The results of the questionnaire served as the class labels of each student in terms of their learning styles for each learning style dimensions. The final data sets were used in data mining.

No.	Student	forum_post	forum_view	self_assesment	text_materials	PROCESSING
1	ABUSTAN, BENELUZ	1	2	8	27	ACTIVE
2	ABUAN, SIDNEY JANE	11	6	3	0	REFLECTIVE
3	ABULAR, MA. FREDA MAE	21	10	7	29	ACTIVE
4	ABULENCIA, APPLE GEM	9	2	8	1	ACTIVE
5	ABUSTAN, AUDREY CASSIE	4	3	8	17	ACTIVE
6	ACERO, CHANTREA FELICHE	15	11	0	14	ACTIVE
7	ADAO, ANTONETTE	22	0	6	4	ACTIVE
8	AGUILA, ELAINE	0	6	0	4	REFLECTIVE
9	ALCANTARA, CHRISTINE JADE	9	7	8	7	ACTIVE
10	ALCANTARA, GABRIEL EMMANUEL	12	5	3	22	REFLECTIVE
11	ALCANTARA, RHEALENE	6	11	2	7	REFLECTIVE
12	ALCOREZA, RONALD	5	12	1	38	REFLECTIVE
13	ALFONSO, ELDRICH CLARK	14	16	2	19	REFLECTIVE

Fig. 4. Excerpt of final data set construction (Processing Dimension)

D. *Feature Selection*

To determine the best features or attributes for determining the learning styles of the students in each dimension, attribute selection was used. Filtering method using Information Gain attribute evaluation was selected. The objective of feature selection technique testing is to empirically confirm and improve the classification performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data. By applying attribute selection, significant predictors were extracted from each mapped attributes for each learning style dimensions. Summary of feature selection results can be seen in Table 3.

TABLE III. RESULTS OF FEATURE SELECTION FOR EACH FSLSM ATTRIBUTES

Information Gain Attribute Evaluation		
Processing Dimension Attributes	**Rank Value**	**Significant? (yes/no)**
forum_view	0.449	yes
self_assessment	0.338	yes
forum_posts	0.267	yes
textual_materials	0	no
Perception Dimension Attributes	**Rank Value**	**Significant? (yes/no)**
concrete_materials	0.345	yes
exercises_rev	0.234	yes
examples	0.108	yes
abstract_materials	0.096	yes
Input Dimension Attributes	**Rank Value**	**Significant? (yes/no)**
video_materials	0.383	yes
visual_materials	0.270	yes
forum_posts	0	no
textual_materials	0	no
Understanding Dimension Attributes	**Rank Value**	**Significant? (yes/no)**
course_overview	0.297	yes
nav_pattern_dist	0.045	yes

Based from the results in Table 3, eleven (11) attribute have been found to be significant in inferring learning styles in LMS.

E. *Pattern Discovery*

In this phase, different classification data mining techniques was applied to the derived data sets. This was needed in order to identify meaningful results from outcomes of the data mining. An open-source data mining software package such as the Waikato Environment for Knowledge Analysis (WEKA) [18] was used to perform data analysis on the derived datasets to discover the most accurate classification model that will be used for the future development of an adaptive LMS for different learning styles. The learning algorithms implemented in WEKA are Neural Network, Naïve Bayes [19], PART and J48 Decision tree classifier [20]. A 10-fold cross validation was used to evaluate the classifier.

F. Evaluation

One of evaluation measure of classification quality in data mining is the Cohen's Kappa Equivalent. It is a coefficient which measures the inter-rater agreement for qualitative categorical items. The measurement was applied to also measure the classification accuracy when performing classification in data mining. Kappa statistics [21] was used to assess the accuracy of any particular measuring cases. Cohen's kappa equivalent values are shown in Table 4.

TABLE IV. COHEN'S KAPPA EQUIVALENT VALUES

Kappa Score	Equivalent
0.81 – 1.00	Perfect
0.61 – 0.80	Substantial
0.41 – 0.60	Moderate
0.21 – 0.40	Slight
<= 0	None

IV. RESULTS AND DISCUSSIONS

To empirically investigate the performance of the classifiers on the extracted data set, algorithms such as Neural Network, Naïve Bayes, PART and J48 Decision Tree are selected. Classification performances are tested on all four dimensions of the FSLSM. The results of the tests are shown in Table 5 and are summarized based on correctly and incorrectly classified instances including Kappa statistics.

Based on the comparative classification performance of different classification techniques, J48 decision tree classifier obtained the highest accuracy with an average of 87.56% collectively for all dimension. The Neural Network, Naïve Bayes and PART yield a collective average accuracy across all learning dimension of 84.58%, 83.22% and 87.22% respectively. Average Kappa Score from the J48 decision tree classifier attained a value of around 0.7205 which shows that the accuracy of classification is 'Substantial'.

TABLE 5. COMPARATIVE PERFORMANCE RESULTS OF CLASSIFICATION USING DIFFERENT TECHNIQUES

Processing Dimension (Active/Reflective)				
	Neural Network	**Naïve Bayes**	**PART**	**J48**
Correctly Classified Instances	88.16%	89.34%	92.25%	**92.30%**
Incorrectly Classified Instances	11.83%	10.65%	7.75%	7.69%
Kappa Statistics	0.762	0.786	0.842	0.845
Perception Dimension (Sensing/Intuitive)				
	Neural Network	**Naïve Bayes**	**PART**	**J48**
Correctly Classified Instances	83.40%	82.40%	88.00%	**89.20%**
Incorrectly Classified Instances	16.60%	17.60%	12.00%	10.80%
Kappa Statistics	0.583	0.587	0.694	0.724
Input Dimension (Visual/Verbal)				
	Neural Network	**Naïve Bayes**	**PART**	**J48**
Correctly Classified Instances	85.20%	85.60%	85.95%	**85.99%**
Incorrectly Classified Instances	14.79%	14.39%	14.05%	14.00%
Kappa Statistics	0.612	0.624	0.651	0.660
Understanding Dimension (Sequential/Global)				
	Neural Network	**Naïve Bayes**	**PART**	**J48**
Correctly Classified Instances	81.56%	75.55%	82.70%	**82.76%**
Incorrectly Classified Instances	18.43%	24.44%	17.30%	17.23
Kappa Statistics	0.630	0.512	0.651	0.653

V. CONCLUSIONS AND FUTURE RESEARCH

This paper is part of an initial stage of the study and is still an on-going research that involves detection of learning styles that classifies student based from their behavior on a Moodle course according to Felder-Silverman Learning Style Model. The selected model is implemented on increased datasets of 565 students enrolled in Computer Programming 1 course in Southern Luzon State University in the Philippines. The results show that the efficiency of classification by means of J48 classification algorithm had the highest average accuracy in terms of correctly classified instances at 87.56%.

In current popular Learning Management Systems, no functions or features are currently available to automatically identify students' individual learning styles that are based from their relative behaviors. This study can be a basis for educators that students' have varied behavior and learning styles. Moreover, this study gives hints to educators to design appropriate course contents that matches the student's learning styles to optimize the learning process.

For future work, the researcher will propose to extend the capability of Learning Management System to adapt its course content to match the learning style of students to respond immediately to their needs based from the model. Also, experimentally apply the adaptive system to test the relationship between learning styles and academic performance.

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